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Discussions

Quantitative comparison between two different methodologies to define rainfall thresholds for landslide forecasting

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Rainfall thresholds for landslide forecasting

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Abstract

This work proposes a methodology to compare the forecasting effectiveness of different rainfall threshold models for landslide forecasting. We tested our methodology with two state-of-the-art models, one using intensity-duration thresholds and the other based on cumulative rainfall thresholds.

The first model identifies rainfall intensity-duration thresholds by means of a software called MaCumBA (MAssive CUMulative Brisk Analyzer) (Segoni et al., 2014a) that analyzes rain-gauge records, extracts the intensities (I) and durations (D) of the rainstorms associated with the initiation of landslides, plots these values on a diagram, and identifies thresholds that define the lower bounds of the I-D values. A back analysis using data from past events is used to identify the threshold conditions associated with the least amount of false alarms.

The second model (SIGMA) (*Sistema Integrato Gestione Monitoraggio Allerta*) (Martelloni et al., 2012) is based on the hypothesis that anomalous or extreme values of rainfall are responsible for landslide triggering: the statistical distribution of the rainfall series is analyzed, and multiples of the SD (σ) are used as thresholds to discriminate between ordinary and extraordinary rainfall events. The name of the model, SIGMA, reflects the central role of the SDs in the proposed methodology.

To perform a quantitative and objective comparison, these two methodologies were applied in two different areas, each time performing a site-specific calibration against available rainfall and landslide data. After each application, a validation procedure was carried out on an independent dataset and a confusion matrix was build. The results of the confusion matrixes were combined to define a series of indexes commonly used to evaluate model performances in natural hazard assessment. The comparison of these indexes allowed assessing the most effective model in each case of study and, consequently, which threshold should be used in the local early warning system in order to obtain the best possible risk management.

In our application, none of the two models prevailed absolutely on the other, since each model performed better in a test site and worse in the other one, depending on the physical characteristics of the area.

This conclusion can be generalized and it can be assumed that the effectiveness of a threshold model depends on the test site characteristics (including the quality and quantity of the input data) and that a validation and a comparison with alternative models should be performed before the implementation in operational early warning systems.

1 Introduction

One of the most widespread methodologies for the forecasting of landslide occurrence is the definition of rainfall thresholds. A rainfall threshold consists on an equation (based on two or more rainfall parameters) that discriminates between the rainfall conditions for which one or more landslides would or would not be triggered.

Since the pioneer works of Endo (1970), Campbell (1975), Lumb (1975), Guidicini and Iwasa (1977) and Caine (1980), the rainfall threshold approach has encountered a great success and many thresholds have been proposed based on a large variety of rainfall parameters (an exhaustive review can be found in Guzzetti et al., 2007). The thresholds based on intensity and duration are probably the most common (Caine, 1980; Guzzetti et al., 2008 and references therein); another very used threshold typology makes use of rainfall amount accumulated over given time periods (Wilson, 2000; Chleborad, 2003; Cardinali et al., 2006; Cannon et al., 2008, 2011) or variable time windows (Lagomarsino et al., 2013).

Independently of the rainfall parameters used to characterize the triggering conditions, every study that made use of both rainfall events that triggered and that did not triggered landslides highlighted that it is impossible to perfectly divide the diagram in a 100 % landslide field and a 100 % non-landslide field (Staley et al., 2013). This brings the necessity of taking a fundamental conceptual decision when defining a threshold:

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a conservative threshold that would encompass every future landslide should be defined or the best trade-off between identified landslides and missed alarms should be researched? It does not exist a universally valid response, as the right answer depends on the objective of the threshold. Indeed, it is important to highlight that thresholds have been proposed and used for two slightly different aims. While some thresholds have been used to identify the minimum rainfall conditions possibly leading to landsliding, others have been specifically designed to be operated in warning systems for civil protection purposes.

The first kind of threshold (minimum thresholds henceforth) is commonly defined as the lower bound to a dataset of rainfall conditions that in the past were associated to landslide triggering (Caine, 1980; Larsen and Simon, 1993; Cannon et al., 2008; Brunetti et al., 2010): it is expected that in the future every landslide will fall above the thresholds. Since minimum thresholds are very conservative, a high number of false alarms is usually expected, because the lower the threshold, the lower the possibility of missing a landslide and the higher the possibility of committing false alarms.

The second kind of thresholds (early warning thresholds henceforth) usually represent the best possible compromise between efficacy in recognizing triggering conditions (for which a low threshold would be preferable) and efficacy in committing a low number of false alarms (for which a high threshold would be preferable) (Martelloni et al., 2012; Staley et al., 2013; Segoni et al., 2014a). In other words, the task of a warning system is to avoid as much as possible both missed alarms and false alarms. Both kinds of errors are considered dangerous as missed alarms may expose society to unrecognized hazards, while false alarms, especially when recurring, may lead to a misperception of risk and to a distrust in the warning system itself (Staley et al., 2013).

The errors committed by a threshold can be recognized and evaluated only if a validation procedure is carried out, but despite rainfall thresholds for the occurrence of landslides are a long debated research topic, only a small number of works complete the presentation of a new threshold with a quantitative validation of its performances

(Martelloni et al., 2012; Staley et al., 2013; Lagomarsino et al., 2013; Segoni et al., 2014a,b; Gariano et al., 2015) or with a comparison with an independent dataset of landslide and rainfall data (Giannecchini et al., 2012). This brings to an additional limitation when a comparison between different thresholds is needed. In fact, while many studies on rainfall thresholds contain a comparison between different literature thresholds (Guzzetti et al., 2007, 2008; Rosi et al., 2012; Chen and Wang, 2014), in most cases this exercise is just a visual comparison of the threshold equations.

Thresholds are very site specific (Segoni et al., 2014b) and the visual comparison of different threshold equations may be interesting from many scientific points of view (e.g. the influence of meteorological regime, landslide typology or other physical features on the threshold equations). However, when a comparison is needed to decide which threshold should be used in a warning system, it is of limited usefulness to compare a threshold obtained using a given methodology in a test site with the threshold obtained with a different methodology in another test site. Moreover, a comparison would be more useful if based on quantitative indexes describing the performances of the thresholds.

This paper explores the aforementioned issues and proposes an approach to quantitatively compare different methodologies for rainfall threshold definition, in order to assess which of them is more suited for the operational use in civil protection warning systems.

Two state of art models based on rainfall thresholds, namely SIGMA (Martelloni et al., 2012; Lagomarsino et al., 2013) and MaCumBA (Segoni et al., 2014a, b) are taken into account and both are applied in two test sites. In each test site, each model undergoes a site-specific calibration to optimize its performance. A validation procedure is carried out on an independent dataset and a confusion matrix is built. The results of the four confusion matrixes (true positives, true negatives, false positives and false negatives) are combined to define some indexes commonly used to evaluate model performances in hazard assessment (Begueria, 2005) and in rainfall thresholds (Martelloni et al., 2012). The comparison of these indexes allowed assessing which model provides the

best performance in each case of study and, consequently, which threshold should be used in the local early warning system in order to obtain the best possible risk management.

2   Material and methods

2.1   SIGMA

This model is based on the concept that landslides occur in the case of rainfall events that can be considered exceptional either for the amount of rain fallen or for the duration: the analysis of rainfall time series allows the identification of extreme events. The distribution of historical rainfall series recorded by a reference rain-gauge was analyzed, considering different periods of accumulation: from 24 h up to 243 days, with daily step (Martelloni et al., 2012). These analyses allow the recognition of anomalous rain values, quantifying the value of the SD of the distribution for each accumulation period. Considering different multiple of SD different thresholds are then defined. The measured and the forecasted rainfall is then compared with these thresholds, according to the algorithm described in Fig. 1, in order to release a daily alert. The thresholds are then calibrated comparing for each territorial unit, the daily model outputs with the corresponding number of occurred landslides: an optimization algorithm identifies the σ curves that minimize the occurrence of false alarm.

The entire territory of Emilia Romagna region is subdivided into 8 Alert Zone (AZ). For each of these different rain gauges are selected, for a total of 25. Each rain gauge is representative of an area called Territorial Unit (TU). The alerts calculated for each TU belonging to the same AZ are then combined to give a single alert for each AZ (Lagomarsino et al., 2013).

The Emilia Romagna regional early warning system is completed by a module that accounts for the effects of snowmelt and snow accumulation (Martelloni et al., 2012) and by a combination with purposely developed landslide susceptibility zonation that

improves the spatial accuracy of the model (Segoni et al., 2014c). However, these additional features are not considered in this work.

2.2 MaCumBA

MaCumBA is based on intensity-duration thresholds, expressed in the form (Caine, 1980):

$$I = \alpha D^{\beta} \tag{1}$$

where I is the rainfall intensity (mm h^{-1}), D is the rainfall duration (h), α (> 0) and β (< 0) are empirical parameters. One of the peculiarities of the MaCumBA model is that thresholds are characterized by a third parameter, called No Rain Gap (NRG). NRG is the number of consecutive hours without rain necessary to separate two rainfall events (Segoni et al., 2014a); this parameter is of fundamental importance to ensure the replicability of the analysis and to consistently employ the thresholds into an operational early warning system.

The procedure for parameters calculation is automated (Segoni et al., 2014a) and it allows handling a large amount of data: starting form a landslide and a rainfall database, a software analyzes each cumulated rainfall recorded in the vicinity of a landslide and the most critical rainfall conditions are identified and characterized in terms of I and D. Once the I and D parameters of every landslide are calculated, they are plotted in a I-D diagram and the threshold that defines the lower bound of the aforementioned values is automatically identified. The procedure is completed by a back-analysis that identifies the NRG value that minimizes the occurrence of errors with respect to landslides and rainfalls occurred during a calibration period.

The model MaCumBA is explained in detail in Segoni et al. (2014a), while Segoni et al. (2014b) discusses its application to the Tuscany region, which was subdivided into 25 Alert Zones, each of them characterized by a specific thresholds. Segoni et al. (2014b) described the integration of the thresholds into the regional warning sys-

tem, which compares the rainfall measured by every rain gauge of the measurement network (about 300 rain gauges) with the proper AZ threshold.

2.3 Similitudes and differences between SIGMA and MaCumBA

Both methods are presently used by regional civil protection agencies for landslide Early Warning Systems (EWS) at regional scale (over $20\,000\,km^2$). SIGMA and MaCumBA operate in the Emilia Romagna region and in the Tuscany region, respectively. They provide automatic outputs, based on the comparison of rainfall thresholds with rainfall forecasts and real time measurements from automated rain gauge networks. Both EWSs are based on a mosaic of local-scale thresholds: the region is subdivided in smaller areas with a site-specific threshold and which are monitored independently. This approach allows accounting for landslides of mixed typology and increases the spatial accuracy.

The main difference between the models lies in the calculation of the thresholds and in the input data required. While SIGMA thresholds are based on cumulative rainfall and consider variable time spans ranging from 1 to 240 days, MaCumBA is based on intensity-duration thresholds. SIGMA requires long rainfall recording (50–60 years time series) but on its basic implementation thresholds can be defined even without landslide data. In turn, MaCumBA needs a complete landslide database to evaluate intensity-duration thresholds, but a shorter period of rainfall data (5–10 years) is required.

To quantitatively compare these two methodologies we applied SIGMA in a Tuscany AZ (Alert Zone, Fig. 3), and MaCumBa in a AZ of Emilia Romagna region (Fig. 2).

3 Application to the ER test site

Emilia Romagna region (Northern Italy) is dominated in the south by the Apennines (Fig. 2). The hilly and mountainous sector extends from the Apennine ridge, in the

SW of the region, to the pede-Apennine margin, in the NE. The chosen Alert Zone, named H, lies in the northwestern part of the region (in red in Fig. 2), and it consists of a hilly zone, with a maximum elevation of about 1000 m. The area is extremely prone to landslide: the most frequent phenomena are deep-seated landslides, mainly rotational-translational slides, slow earth flows and complex movements (Bertolini and Pellegrini, 2001; Bianchi and Catani, 2002). Rapid shallow landslides are less recurrent but their frequency is significantly increasing in the last few years (Martina et al., 2010).

The application of SIGMA in Emilia Romagna is already published (Martelloni et al., 2012; Lagomarsino et al., 2013) and considers the timespan 2004–2007 as the calibration period and the timespan 2008–2010 as the validation period.

Using the same timespans and datasets, the MaCumBA model has been applied to the AZ H of Emilia Romagna region. The dataset consists in 71 landslides occurred in the period 2004–2007 and in the measurements of 9 automated rain gauges (Fig. 2).

The application of MaCumBA resulted in a threshold represented by the equation

$$I = 22.46D^{-0.639} \tag{2}$$

This threshold is also reported in Fig. 3, where the events used for its definition are also represented.

4 Application to Tuscany test site

Tuscany region is located in Central Italy and it is characterized by a mainly hilly and mountainous territory (Fig. 4). The alert zone (AZ) chosen as test site for comparing the two different methodologies corresponds with the Serchio basin and includes part of the northern Apennines, a fold ant thrust post collisional belt. This area is mainly mountainous and shows two different geological settings (Rossi et al., 2013): in the western sector, mountain tops are mainly made up of carbonaceous rocks and have very steep flanks. The summits are typically connected to the lower parts of the slopes, composed of metamorphic sandstone and phyllitic-schist, by talus and scree deposits.

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The eastern sector shows a more uniform geological condition with the prevalence of flysch formation rock type.

The application of MaCumBA in Tuscany and in the Serchio alert zone is already published (Segoni et al., 2014a) and considers the timespan 2000–2007 as the cali-
⁵ bration period and the timespan 2008–2009 as the validation period.

Using the same timespans and datasets, the SIGMA model has been applied to the Serchio AZ of Tuscany region. The dataset consists in about 700 landslides occurred in the period 2000–2007 and in the measurements of 37 automated rain gauges (Fig. 2). However, most of these instruments were installed in recent times, and only three of
¹⁰ them have long enough time series (between 60 and 70 years) (Fig. 2). SIGMA model was applied separately for each rain gauge and it was verified that the best results can be obtained using Gallicano as the only reference rain gauge for the whole AZ (Fig. 4). After the calibration procedure against the available landslide dataset, the thresholds shown in Fig. 5 were selected as the optimal ones for this AZ.

¹⁵ **5 Results**

The results obtained applying the two different methodologies in the two test sites are summarized in contingency matrixes that indicate the number of days with landslides correctly detected by the models, the number of days in which an alarm was forecasted but no landslides occurred (false alarms), the number of days in which landslides oc-
²⁰ curred but the model did not forecast them (missed alarms), and the number of rain-
fall days without landslides correctly predicted. The results of the four confusion ma-
trixes were combined to define some indexes commonly used to evaluate model perfor-
mances in hazard assessment (Begueria, 2005) and in rainfall thresholds (Martelloni et al., 2012). These indexes quantify the forecasting effectiveness of the models in the
²⁵ different test sites and allow a rigorous comparison of the performances.

The efficiency index represents the ratio of correct prediction respect to the total. The closer to 1, the better the model. Positive and negative predictive power indexes are

the proportions of positive and negative results that are true positive and true negative results. Sensitivity (also called the true positive rate) measures the proportion of actual positive occurrences (landslides) which are correctly identified as such. Specificity (also called the true negative rate) measures the proportion of negatives occurrences (days without landslides) which are correctly identified as such. A perfect predictor would be described as 100 % sensitive and 100 % specific; in a warning system the best possible trade-off between sensitivity and specificity is desirable. The likelihood ratio evaluates in a single parameter both the sensitivity and the specificity and the higher its value, the better the model.

The outcomes of the Emilia Romagna test site are summarized in Tables 1, 2 and 3. The SIGMA results are yet published in Lagomarsino et al. (2013).

The validation results of the Tuscany test site are reported in Tables 4, 5 and 6.

6 Discussion

The confusion matrixes and the derived validation indexes provide an objective basis for the comparison of the different methodologies.

Considering efficiency (that balances positive and negative predictive power) and likelihood ratio (that balances sensitivity and specificity), we can conclude that none of the two models can be considered better than the other. Indeed, in each test site the purposely developed model prevailed on the other: in Tuscany the best outcomes were obtained by MaCumBA (likelihood ratio value 158.6 vs. 11.8 and efficiency 0.98 vs. 0.92), whereas in Emilia Romagna SIGMA prevailed with a 89.8 likelihood ratio value (vs. 51.3) and efficiency values almost equal.

It is evident that the best results are obtained with the model specifically conceived for the physical features of the case of study. Among these features, the different landslides typologies chiefly influence the performance of the models: MaCumBA, which is based on intensity-duration thresholds, prevails in the Serchio valley that is affected mainly by shallow landslides; SIGMA is based on a complicate decisional algorithm

conceived to account for both shallow and deep seated landslides, and it prevails in the Emilia Romagna test site, which is affected by both typologies of landslides.

Results show that the both threshold models are characterized by satisfactory results: in all applications, the validation statistics are close to optimal values. This outcome proves the exportability of both models.

7 Conclusions

Rainfall thresholds are widely used in landslide forecasting and they often constitute the core of civil protection warning systems. However, most of the rainfall thresholds presented in the literature rarely underwent a rigorous validation procedure. Moreover, to date no publication exists that rigorously compares two or more different rainfall threshold models in order to choose for an early warning system the approach with the best forecasting effectiveness.

This paper proposes a methodology to compare different rainfall threshold based approaches and to assess which of them is the best to be used in a specific warning system.

An important outcome of this work is that a consistent comparison between different early warning systems goes beyond a simple comparison between the respective literature thresholds. Indeed, it is the methodology to define rainfall thresholds that needs to be compared. Therefore, different methodologies need to be applied in the same test site, the respective thresholds need to be calibrated against the data at hand, and a validation procedure against an independent dataset is needed to define objective and quantitative indicators of their performance and to perform a comparison.

We tested two different early warning systems, SIGMA (Martelloni et al., 2012) and MaCumBA (Segoni et al., 2014a), which are already operating in two different Italian regions, Emilia Romagna and Tuscany, respectively. To compare these two methods, each of them was applied in a part of the region in which the other is active.

The two different techniques gave good results even in the areas different from those for which they have been originally conceived and implemented. This proved the exportability and replicability of the approaches. However, in each test site the best results were obtained by the EWS that is already operational in the region. This means that none of the two models prevailed absolutely on the other: each model performed better in a test site and worse in the other one, depending on the physical characteristics of the area. In the test site affected by shallow landslides, intensity-duration thresholds provided the best outcomes, while in the test site affected by both shallow and deep seated landslides the best results were obtained using a more complex decisional algorithm based on rainfall amounts as measured over variable time windows.

This conclusion can be generalized and it can be assumed that the effectiveness of a threshold model depends on the test site characteristics (including the quality and quantity of the input data) and that a validation and a comparison with alternative models should be performed before the implementation in operational early warning systems.

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Table 1. Contingency matrix displaying the results obtained applying MaCumBA in the Emilia Romagna test site.

Emilia Romagna test site MaCumBA model		Observed truth	
		Landslide	No Landslide
Prediction	Landslide	*6*	*7*
	No Landslide	**12**	*1071*

Table 2. Contingency matrix displaying the results obtained applying SIGMA in the Emilia Romagna test site.

Emilia Romagna test site SIGMA model		Observed truth	
		Landslide	No Landslide
Prediction	Landslide	*18*	*12*
	No Landslide	**0**	*1066*

Table 3. Validation statistics and comparison of the performances of the two models in the Emilia Romagna test site.

Emilia Romagna test site	Efficiency	Positive predictive power	Negative predictive power	Sensitivity	Specificity	Likelihood
MaCumBA	0.98	0.46	0.99	0.33	0.99	51.3
SIGMA	0.99	0.6	1	1	0.99	89.8

Table 4. Contingency matrix displaying the results obtained applying MaCumBA in the Tuscany test site.

Tuscany test site MaCumBA model		Observed truth	
		Landslide	No Landslide
Prediction	Landslide	*18*	*1*
	No Landslide	**3**	*184*

Table 5. Contingency matrix displaying the results obtained applying SIGMA in the Tuscany test site.

Tuscany test site SIGMA		Observed truth	
		Landslide	No Landslide
Prediction	Landslide	*19*	*12*
	No Landslide	**2**	*144*

Table 6. Validation statistics and comparison of the performances of the two models in the Tuscany test site.

Tuscany test site	Efficiency	Positive predictive power	Negative predictive power	Sensitivity	Specificity	Likelihood
MaCumBA	0.98	0.95	0.98	0.86	0.99	158.6
SIGMA	0.92	0.61	0.99	0.9	0.92	11.8
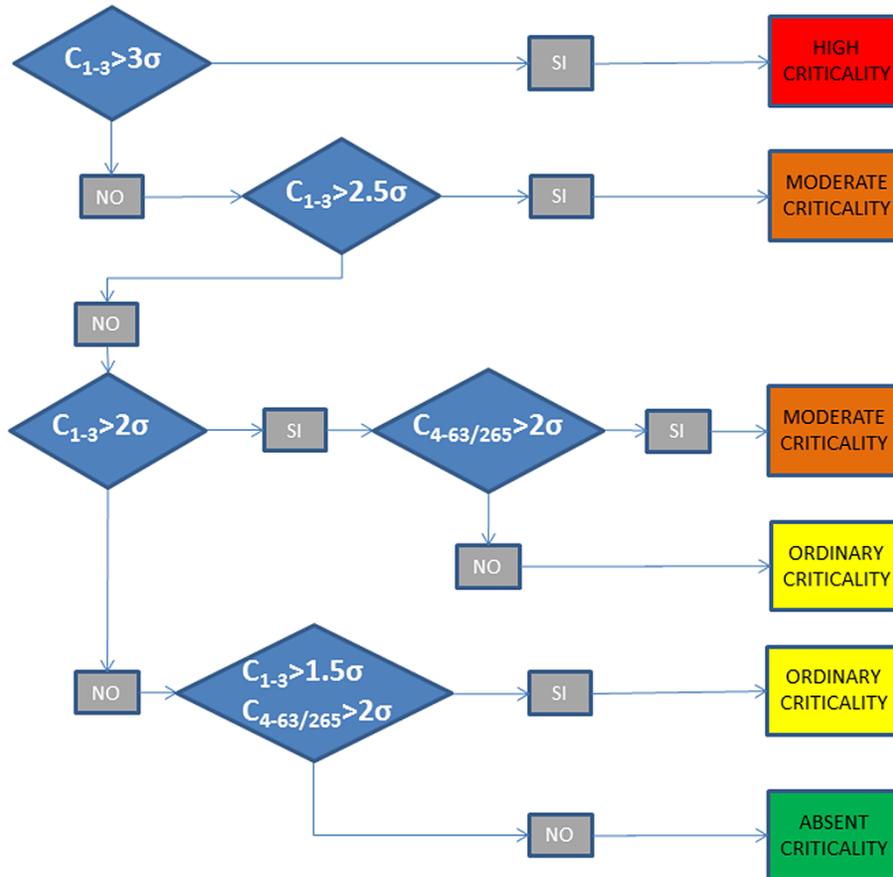
Figure 1. SIGMA algorithm (modified after Martelloni et al., 2012).
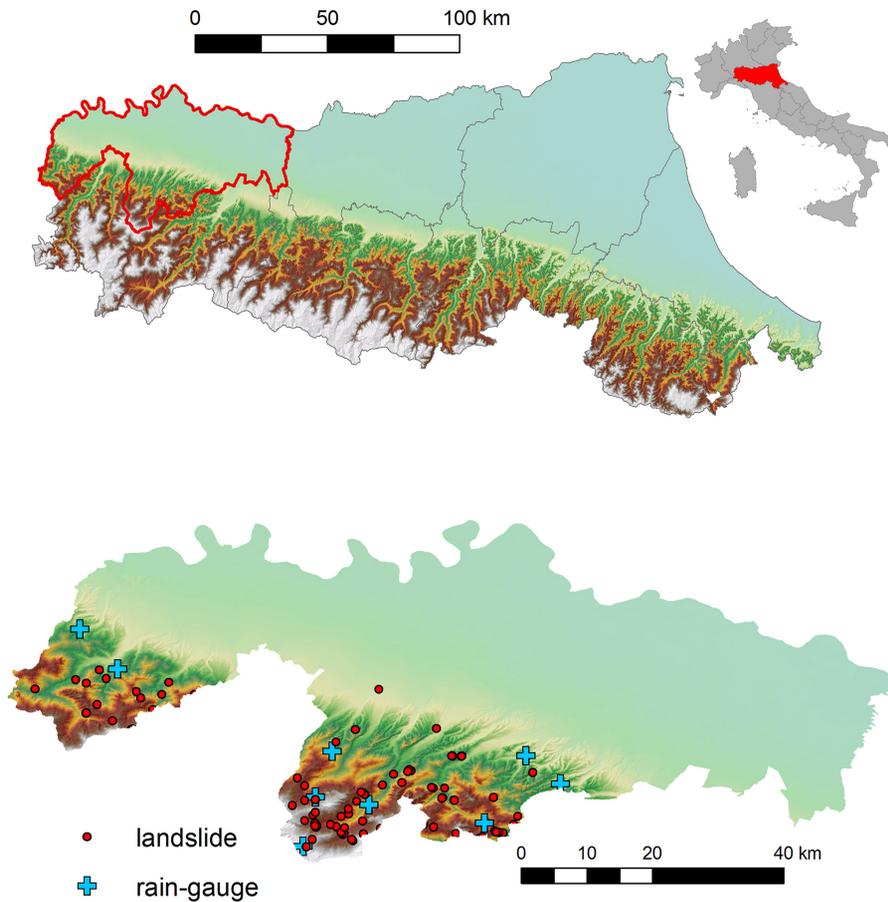
Figure 2. Emilia Romagna region. Rain gauges in the test site (blue cross), and landslides recorded in the period 2004–2010 (red circles).

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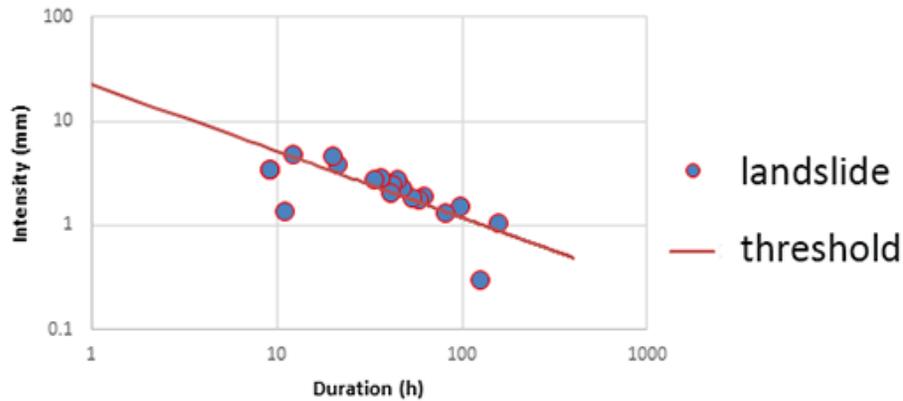
Figure 3. *I-D* threshold evaluated by MaCumBA for the Emilia Romagna test site.

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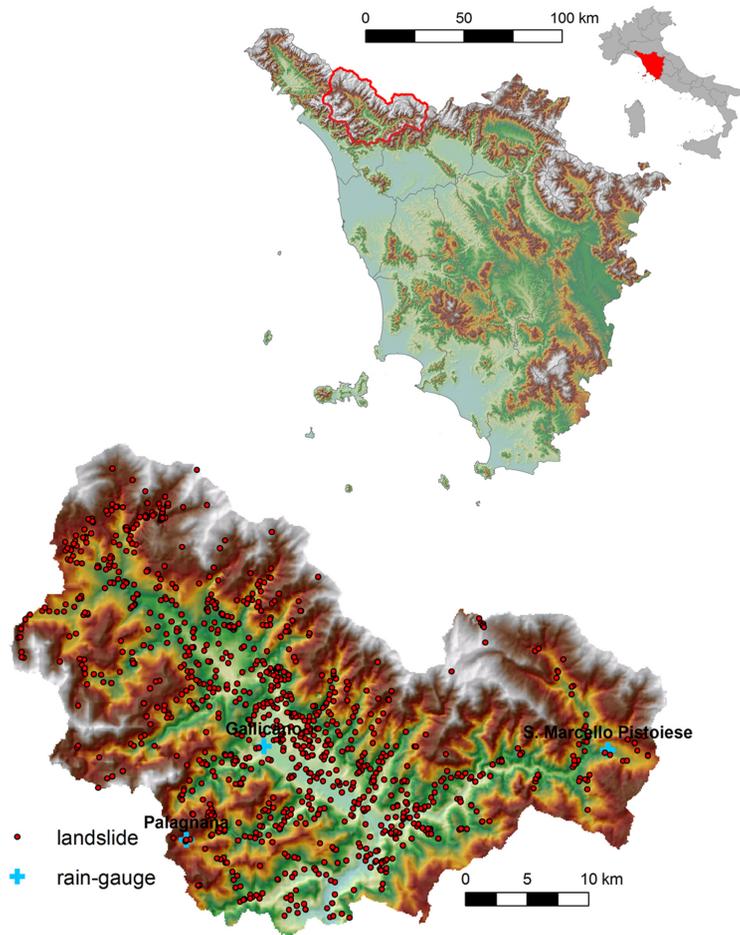
Figure 4. Tuscany region, with a zoom on the Serchio basin test site.
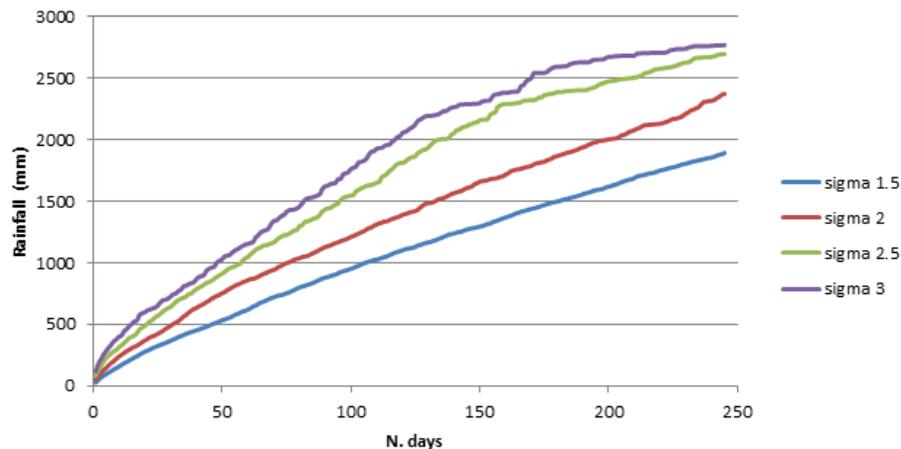
Figure 5. Rainfall threshold obtained with the SIGMA model in the Serchio AZ.

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